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SOC Estimation of E-Vehicle Using Large Dataset for Vehicle Energy Consumption

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Abstract:
The sale of electric vehicles in the market still faces a challenge due to their limited driving range, in addition to the time required for charging batteries and, in many cases, the limited infrastructure of charging stations. Each time, before starting a journey, the driver has to assess whether the available charge on the battery is enough or not. Frequently, this estimation is based on the travelling distance and past consumption. There are two aspects that can have a very significant influence on the battery consumption: the route and the driving style. Accuracy of battery charge status (SOC) estimation plays a significant role in the management of electric vehicle power batteries. However, recently abrupt changes from SOC data often occurs in the actual operation of electric vehicles and some errors appear in the establishment of battery models which gives rise to poorly adaptive and robust performance of traditional algorithms in the process of SOC estimation. The work proposed in this paper uses a RNN-LSTM based model which can effectively improve the accuracy of models and SOC estimation of lithium ion batteries.

Keywords: *Automated Vehicles, Deep learning, Electric Vehicles, LSTM, RNN, SOC.*

I. Introduction

Using machine learning and related methods in the area of EV energy use has not yet gained a lot of attention. Deep learning is now finding usage in many automotive applications. With the advancements and research in the autonomous driving and electrification of vehicles, the deep learning algorithms play a major role in electric vehicles systems. The electric vehicle is gaining pace with the need for clean energy to be used in vehicles which also reduces exhaust from vehicles. Deep Learning (DL) has also made a positive impact on the control of automatic vehicles (AVs), particularly in terms of the steering angle prediction due to its ability to effectively process unlabelled raw data. We identify it into two classes of studies:

- those related to the energy use by the vehicles themselves and;
- those related to EV charging infrastructure.

For Electric vehicles, the major source of power is the battery and hence there is a need to reduce the power consumed by the electronic components in the vehicle. The electric motor power consumption needs to be optimized, for electric vehicles to be more effective. For effective optimization, the vehicles power behaviour has to be identified, predicted and using this as the input, decisions can be taken like when more or less power is required by the motor. The vehicles are equipped with Electronic Control Units(ECU) to which the decision output can be provided to control the motor speed based on the power demand predicted at the time. For this, one can use deep learning algorithms to perform the complex task and take decisions. Deep learning algorithms simplify the complex task of decision making by using the past data from the training set. The most important inputs to the deep learning are identifying the right data for the training so that the network can train and can predict the outcome when the actual data is fed. Neural Network is the backbone of deep learning. One of the most commonly used algorithms for deep learning is the Recurrent Neural Networks. For dynamic input data, typical Feed Forward Neural networks cannot be used as this type of networks are static after training with data. The Recurrent Neural networks are ideal for dynamic and changing inputs in which the networks adapt to the dynamic change in the inputs. A much more advanced algorithm of RNN is Modular Recurrent Neural networks (MRNN) [1] [2], which is ideal for networks that have more dynamic parameters needed to be predicted. In [3], a deep learning algorithm based on Modular Recurrent Neural Network (MRNN) is used to train vehicle power behaviour. For the vehicle power predictions and deriving a data set for the training network, a mathematical model of a vehicle is required with vehicle parameters. In [4] [5] [6], a simple model of vehicle is considered. From the vehicle model, a simple data set is used for training the network and the trained network is used to predict the actual data.

II. Related Work

Apart from the literatures on EV's a great amount of work can also be found in the area of unmanned vehicle (autonomous driving). Neural networks can learn complex interactions between features, which is beneficial for autonomous driving in dynamic environments [7]. Steering a car through traffic constitutes a complex task that is very hard to cast into algorithms. Thus, researchers turn to train Artificial Neural Networks (ANN) with a stream of data generated by front-facing cameras yielding associated steering angles [8]. The benefits of steering angle prediction using the DL approach are that it has tolerance for mistakes, the ability to quickly identify errors and better capability in managing unpredictable situations [9]. Different studies have applied various algorithms to achieve these goals. For instance, in the literature [10–12], the authors propose a Genetic Algorithm (GA) for steering control. Linhui and Lie [13] worked on control of unmanned vehicles using fuzzy logic via GA. Layne and Passino [14] worked on fuzzy logic model-based control learning for cargo ship steering. Cao et al. [15] worked on a system for controlling brake pressure based on fuzzy logic using steering angle and yaw speed. Lee [16] proposed a steering autopilot control algorithm for four-wheel-steering passenger vehicles. A major setback of fuzzy logic is that the use of fuzzy logic-based controllers for rear-end collision avoidance depends on the number of fuzzy rules, and an extreme amount of such rules has direct bias on its efficiency [17]. Many studies have applied DL in predicting the steering angle of AVs [18–22]. Kuutti et al. [23] and Oussama and Mohamed [24] surveyed DL applications in AV control.

The modelling of EV infrastructure starts from modelling the energy use of the charging stations [25]. Such studies are also extended to optimize scheduling of the charging times using actor-critic learning [26. While the total energy use is proportional to the number of EVs within some region, the energy use prediction for individual charging stations is more complicated [27]. Other type of problems concerns modelling the individual energy use for a specific EV instance. Various management strategies are proposed using reinforcement learning to transfer efficient energy management from expected velocity to automated system control [28-29]. The authors [30] model the vehicle energy consumption in terms of the state-of-charge by minimizing the so-called Q-function using reinforcement learning. Liu et al. considered the speed profile as input to predict the state-of-charge (SOC) as output. Deep learning applied on increased quantities of historical data enables modelling of EVs based on driver's history [31, 32], and on predetermined fixed routes [33]. The probabilistic energy prediction approach [34] was investigated by creating statistical models. The authors [35] use probabilistic models on sequence data inspired by the works that are related with time-to-event churn prediction or asset management [36]. Some researchers combine this approach with the recurrent models which are successfully used on spatio-temporal data in predicting extreme condition traffic [37] or origin-destination forecasting [38].

With the fast development of the EV industry, it is bound to encounter new challenges to the power sector industry due to the large capacity of the battery and stochastic charging behaviour of the users. High EV penetration may substantially increase the electricity usage and peak power demand in high adoption areas. Therefore, an accurate EV charging-power demand forecast system needs to be developed in order to evaluate the impact of charging EV batteries on the power systems. In this regard, accurate short-term load forecasting is a key measure to the intelligent control of EV charging systems. Power load forecasting models can be categorized into traditional statistical models and artificial intelligence models, traditional forecasting methods include time series method [39], autoregressive integrated moving average [40], regression analysis [41], Kalman filtering [42], etc. Artificial intelligence methods include artificial neural networks [43], support vector machines [44], and deep learning methods [45]. Before the 21st century, due to strong adaptive, self-learning and generalization ability of artificial neural networks (ANN), it had become a hot research topic for adopting ANN approaches in load forecasting. The article [46] reviewed the application of ANNs for load forecasting and proved that ANNs have effectiveness for load forecasting in terms of accuracy and efficiency. In recent years, thanks to the breakthrough of computing hardware and successful applications such as Alpha-go, the deep learning methods have obtained wide attractions and are used in image semantic segmentation [47], image classification [48], target detection [49], natural language processing [50] and many other science and engineering fields.

In two studies [51,52], real traffic and charging data influenced by weather data were considered in determining the EV charging-power demand. In addition, the integration of sustainable mobility, stationary energy storage systems, and renewable energy sources were also studied in [53–57]. Studies [55-57] presented the integration of renewable energy sources in the EV charging infrastructures. However, most previous works have investigated settings that consider private charging stations and a fixed charging-start time. While such settings are valid for predicting the charging-power demand of EVs that are parked at a private charging station during a specified time duration (e.g., vehicles that are charged at homes or at workplaces), such settings cannot be used to characterize the charging-power demand of EVs that are charged at public fast-charging stations. Therefore, models that characterize the time-spatial charging-power demand of EVs at public charging stations should be developed so that the EV charging-power demand can be predicted more accurately and reliably. However, only a few studies [58-62] have presented a time-spatial EV charging–power demand prediction model. Bae and Kwasinski [59] presented a time-spatial EV charging-power demand anticipation study that considered a Poisson-distributed vehicle arrival rate at fast-charging stations near highway exits, and estimated the EV charging-power demand based on an M/M/ s queueing theory. Shrestha and Hansen [60] presented a state-transition algorithm that was used to develop a stochastic model of EV movement in an integrated traffic and power network. Considering the increased use of EVs in metropolitan cities, researchers [58,61,62] also studied EV charging-power demand models for urban zones. Mu et al. [58] developed a time-spatial model that integrated a transportation analysis into a power-system analysis. Zhou and Lin [61] presented a time-based EV charging-power demand forecast model with multiple charging stations in urban areas. They anticipated the EV arrival rate at a charging station with a cell-transmission traffic model and used an M/M/s queue for the EV charging service. Viswanathan et al. [62] evaluated the time-spatial aspect of the charging-station placement using modelling and simulation based on real-world traffic data. As the EV penetration rate increases, the need for developing time-spatial EV charging-power demand models that consider the uniqueness of urban areas is expected to grow. The rather high complexity of road networks and traffic flow in realistic urban areas is expected to introduce challenges for applying the models and approaches of previous studies. In addition, EV charging power demand models for urban areas should consider that the road system is populated with vehicles, and EV users can charge their EVs at a fast-charging station whenever they have not charged their batteries at home or work. Although using EVs in urban neighbourhoods is expected to be non-negligible, only a few studies [58,61,62] on determining the EV charging-power demand in urban areas have been reported. In contrast, the random forest algorithm (RF) used in [63] has been applied to power load forecasting from user-side, and the parallelized data processing mode implemented by random forest has the characteristic of high efficiency.

The influence of the route characteristics on the fuel or energy consumption of a vehicle is evident. Moreover, one can find several studies showing the influence of driving style. Thus, in [64] driving aggressiveness is correlated with some variables such as speed, longitudinal acceleration and lateral acceleration. Assuming that aggressiveness acts as a linear filter on these signals, the model is validated through some trials in which drivers sometimes behave gently and sometimes aggressively. All previous studies focused on conventional vehicles. However, [65] [66] attempt to predict the charge consumption of an electric vehicle using an Artificial Neural Network. Another novel aspect is that the data acquisition was performed using a smartphone. The input variables of the neural network are speed, accelerations and jerks and predictability of the system amounted to over 95%.

This work [67] intends to eliminate the limitations on the choice of the route used by earlier studies. Thus, it is intended to analyse the influence of the different driving styles when predicting the consumption of an electric vehicle through a neural network trained with traffic data in urban environment. The data is obtained from tests carried out on a sample of drivers, in order to predict the energy consumption when covering a specific route by a driver whose driving parameters have been measured previously. A system based on a Neural Network using kinematic driving data and route data to estimate the consumption of battery charge is proposed. The method used is based on two phases. *Phase 1: Neural Network training:* Driving variables of different users for different routes and consumption of battery charge are recorded. To train the network, data of all drivers circulating along various routes are used in order to cover the widest variability.

Phase 2: Validation and application of the Neural Network: The driving variables for each registered user in phase 1 are considered as the characteristics of their driving style and these variables are used as inputs to the network when applying it to a new route. The input vector is completed with route variables. The functioning of the network is validated with tests on other routes than those considered in phase 1, followed by measuring and comparing actual consumption with the network estimations.

III. Proposed Method

In real-world, vehicle energy consumption is affected by various other factors including other road users, traffic signals, road conditions, road grade, heating and ventilation. A number of real-world traffic data are available to the public. The case studies are supplemented with a number of examples to demonstrate how Vehicle energy dataset (VED) can be utilized for vehicle energy and behaviour studies. Potential research opportunities include data-driven vehicle energy consumption modelling, driver behaviour modelling, machine and deep learning, calibration of traffic simulators, optimal route choice modelling, prediction of human driver behaviours, and decision making of self-driving cars. We believe that VED can be an instrumental asset to the development of future automotive technologies. The dataset can be accessed at https://github.com/gsoh/VED.

Taking into consideration the relative rarity of these vehicles, as a part of the effort, a small data of 772 studies containing nearly 42070 samples were identified and used for the study. OBD-II provides information on the status of the various vehicle subsystems, via a standardized communication protocol. The OBD-II port provides an entry point to the vehicle Controller Area Network (CAN), enabling CAN signals to be monitored and recorded.The dataset consists of two primary components: (1) static data and (2) dynamic time-series data. Static data include vehicle parameters shown in Table I;

Table IStatic Data

Parameters	**Example**
Vehicle Type	ICE Vehicle, HEV, PHEV, EV
Vehicle Class	Passenger Car, SUV, Light truck
Engine Configuration	I4, V4, V4 Flex, V6 PZEV
Engine Displacement	1.0L, 2.0L, 3.6L
Transmission	5-SP Automatic, 4-SP Manual, CVT
Vehicle Weights	3,000lb, 5,000lb
Drive Wheels	FWD, AWD

Dynamic data include time-stamped naturalistic driving records of the fleet. The list of dynamic signals, described in Table. II, are categorized into the three groups: GPS signals, standard OBD-II signals, and OEM-customized OBD-II signals.

Table II Dynamic Data

	Data
GPS	Latitude / Longitude (deg)
Engine Information (standard OBD-II signals)	Vehicle Speed (km/h)
	Engine RPM (rev/min)
	Fuel Info Mass Air Flow (g/s)
	Fuel Rate (L/h)
	Absolute Load
	Short Term Fuel Trim B1 (%)
	Short Term Fuel Trim B2 (%)
	Long Term Fuel Trim B1 (%)
	Long Term Fuel Trim B2 (%)
	Outside Air Temperature (∘ C)
	Auxiliary Power (HVAC)
	AirCon Power (KW)
	AirCon Power (W)
	Heater Power (W)
Battery Information (OEM-customized OBD-II signals)	Battery SOC (%)
	Battery Voltage (V)
	Battery Current (A)

Among the broad range of OEM-customized OBD-II signals, our interest lies in the information collected on battery usage and auxiliary power consumption. Battery Current and Battery Voltage indicate DC current and voltage measured at the high voltage terminal. While Battery Voltage can only have non-negative values, Battery Current can be positive (charging) or negative (discharging). Battery SOC is the state of charge of the high voltage battery as a percentage of maximum battery capacity. AirCon Power and Heater Power represent the power consumed by the AC compressor and the electric heater, respectively.

For simulating the SOC, RNN-LSTM model is used. RNN is composed of input layer X, hidden layer Y and an output layer H. Compared to CNN, RNN retains historical information and is widely used to solve time series data problems. However, RNN has a problem of gradient explosion and gradient disappearance, so it can only deal with shorter timing problems. The research of LSTM (Long Short Term Memory) networks can effectively improve the hidden nodes of RNN and provide a new direction for solving the problems of time series prediction. Combining RNN and LSTM can make full use of the input data features while saving historical input information, which has a more accurate and stable prediction effect.

RNN with four hidden LSTM layer was devised and the code was written in google colab. Each hidden layer consists of 50 neurons. For the training samples, we decided to divide trials in temporal windows of 5 minutes and calculate the variables for each of these windows. This is done to provide a larger number of samples from which the network can learn. Furthermore, such a division can capture more driving situations. With this process, from 772 trials considered for the training process, a total of 42070 samples are obtained with 22 different parameters including Vehicle ID, timestamp, Battery SOC, Battery voltage, Battery current etc. The 772 case studies were randomly divided so that 712 of them are integrated into the training set and remaining 100 in the validation set.

IV. Results

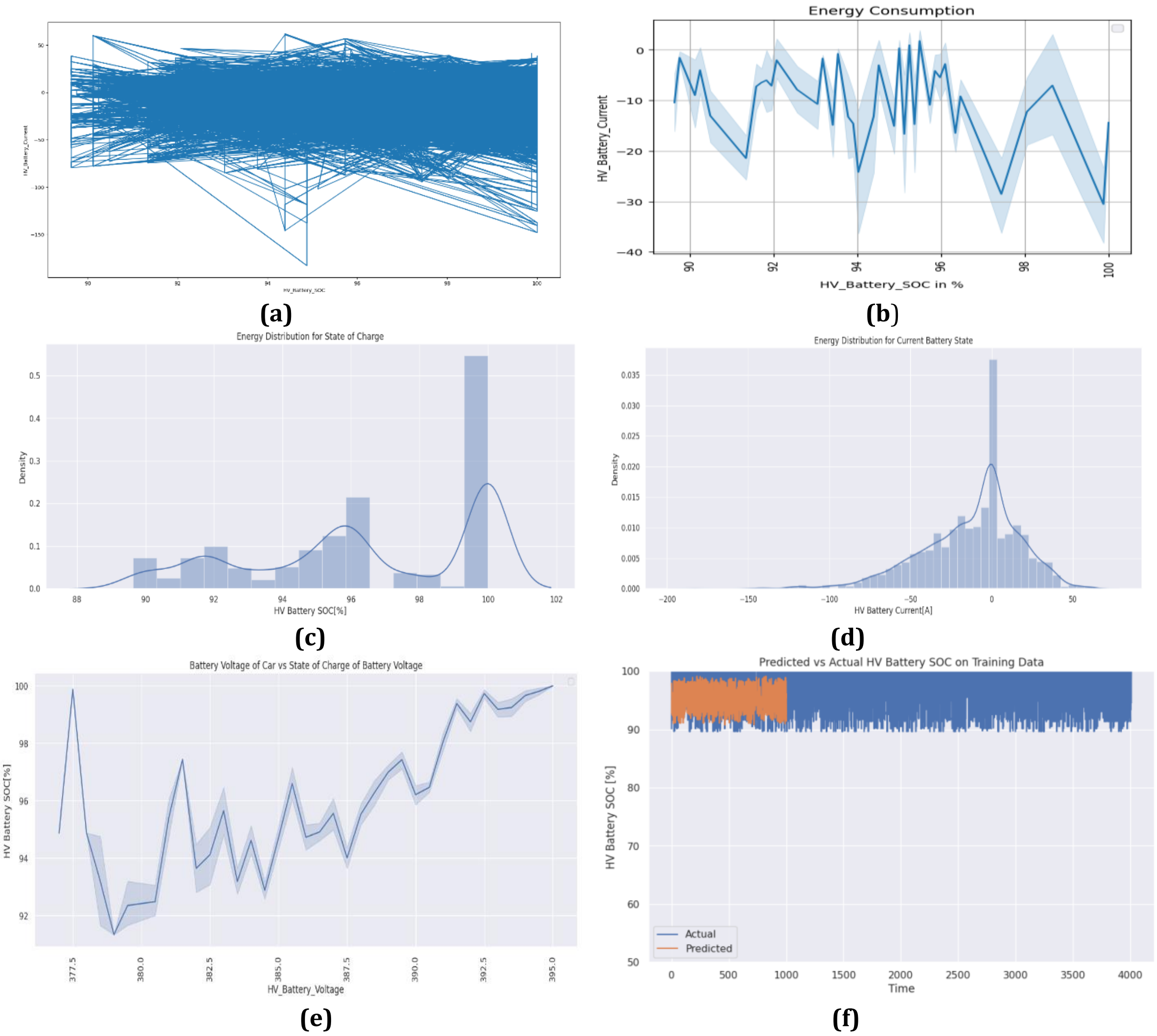

Fig 1 (a) Battery SOC Vs Battery current (b) Energy Consumption (c) Energy distribution for SOC (d) Energy distribution for current battery state (e) Battery voltage Vs SOC (f) Predicted Vs actual Battery SOC

Battery is the major component of an electric vehicle. Energy consumption of a battery therefore governs the usefulness of an EV. Battery SOC plays a major role in the analysis of an EV. The coulomb counting method, also known as the ampere hour counting and current integration is the most common technique for calculating the battery SOC. The method employs battery current readings mathematically integrated over the usage period to calculate SOC given as;

$$\text{SOC} = \text{SOC(to)} + \frac{1}{Crated}\int_{to}^{to+\tau}(Ib - Iloss)dt \qquad (1)$$

Where SOC(to) is the initial SOC, C_{rated} is the rated capacity, I_b is the battery current and I_{loss} is the current consumed by the loss reactions. Fig 1(a) represents the battery current plotted as a function of battery SOC for ---- vehicles. Fig 1(b) determines the energy consumption where battery current is plotted as a function of SOC in %.
Fig 1(c) and (d) represent the energy distribution for state of charge and current battery state respectively.

The SOC of a battery that is its remaining capacity can be determined using a discharge test under controlled conditions. The voltage method converts a reading of the battery voltage to the equivalent SOC value. Using the known discharge curve (voltage Vs SOC) of the battery (Fig 1 (e)). However, the voltage is significantly affected by the battery current due to the batteries electrochemical kinetics and temperature.

Fig 1(f) represents the predicted SOC against actual SOC. The RNN-LSTM model predicted a battery SOC of 97.86796

V. Conclusion

Accuracy of battery charge status (SOC) estimation plays a significant role in the management of electric vehicle power batteries. However, recently abrupt changes from SOC data often occurs in the actual operation of electric vehicles and some errors appear in the establishment of battery models which gives rise to poorly adaptive and robust performance of traditional algorithms in the process of SOC estimation. The work proposed in this paper can effectively improve the accuracy of models and SOC estimation of lithium ion batteries is predicted to be 97.86796. Battery overcharging and over-discharging can be avoided because of the accuracy of battery SOC estimation, which helps to achieve battery balance and provides important data support for the calculation of Electric vehicle mileage.

References:

[1]. YanjunLi, Guodong Yin, Weichao Zhuang, Ning Zhang, Jinxiang Wang, and Keke Geng," Compensating Delays and Noises in Motion Control of Autonomous Electric Vehicles by Using Deep Learning and Unscented Kalman Predictor", IEEE Trans On Systems man and cybernetics, issue. 99, pp.1-13, July.2018.
[2]. NimaMohajerin, Steven L. Waslander, "Modelling a Quadrotor Vehicle Using a Modular Deep Recurrent Neural Network", IEEE International Conference on Systems, Man, and Cybernetics, pp.376-381, Oct.2015.
[3]. NimaMohajerin, Steven L. Waslander, "Modular deep RecurrentNeural Network: Application to quadrotors", IEEE International Conference on Systems, Man, and Cybernetics, pp.1374-1379, Oct2014.
[4]. Mojtaba Alizadeh, Shokrolah Shokri Kojori, Soheil Ganjefar," A Modular Neural Block to Enhance Power System Stability", IEEE Transactions on Power Systems, vol28, issue4, pp.4849-4856, Oct2013.
[5]. [5] Sebastian Ciceo, Yves Mollet, Mathieu Sarrazin, Johan Gyselinck, Herman Van der Auweraer, Claudia Martis,, 2016 IEEE 16th International Conference on Environment and Electrical Engineering, pp.1-4, Jun. 2016.
[6]. Zhoubo Ding, Liping He, Zuoming Dong," Modeling and testing of low speed electric vehicle", International Conference on Electric Information and Control Engineering, pp.235, 2011
[7]. F. Mohseni, S. Voronov, and E. Frisk, ''Deep learning model predicitive control for autonomous driving in unknown environments,'' IFAC PapersOnLine, vol. 51, no. 22, pp. 447–452, 2018.
[8]. H. M. Eraqi, M. N. Moustafa, and J. Honer, ''End-to-end deep learning for steering autonomous vehicles considering temporal dependencies'', arXiv:1710.03804. [Online]. Available: http://arxiv.org/abs/ 1710. 03804, 2017.
[9]. [9] M. Z. Islam, ''Self-driving car: A step to the future of mobility,'' BRAC Univ., Dhaka, Bangladesh, Tech. Rep. 10361/11027, 2018.
[10]. B. Krogh and C. Thorpe, ''Integrated path planning and dynamic steerring control for autonomous vehicles,'' in Proc. IEEE Int. Conf. Robot. Automat. pp. 1664–1669, Apr. 1986
[11]. E. W. McGookin, D. J. Murray-Smith, Y. Li, and T. I. Fossen, ''Ship steering control system optimisation using genetic algorithms,'' Control Eng. Pract., vol. 8, no. 4, pp. 429–443, Apr. 2000.
[12]. H.-S. Tan, J. Guldner, S. Patwardhan, C. Chen, and B. Bougler, ''Development of an automated steering vehicle based on roadway magnets—A case study of mechatronic system design,'' IEEE/ASME Trans. Mechatronics, vol. 4, no. 3, pp. 258–272, Sep. 1999.
[13]. L. Guo, P. Hu, R. Wang, L. Li, M. Zhang, and L. Guo, ''Study on lateral fuzzy control of unmanned vehicles via genetic algorithms,'' J. Mech. Eng., vol. 48, no. 6, pp. 76–82, Jun. 2012.
[14]. J. R. Layne and K. M. Passino, ''Fuzzy model reference learning control for cargo ship steering,'' IEEE Control Syst., vol. 13, no. 6, pp. 23–34, Dec. 1993.
[15]. C.-T. Cao, ''System for controlling brake pressure based on fuzzy logic using steering angle and yaw speed,'' Google Patent 5 634 698, Jun. 3, 1997.

[16]. A. Y. Lee, ''A preview steering autopilot control algorithm for four-wheel-steering passenger vehicles,'' J. Dyn. Syst., Meas., Control, vol. 114, no. 3, pp. 401–408, 1992.
[17]. S. Khadim, F. Riaz, S. Jabbar, S. Khalid, and M. Aloqaily, ''A non-cooperative rear-end collision avoidance scheme for non-connected and heterogeneous environment,'' Comput. Commun., vol. 150, pp. 828–840, Jan. 2020.
[18]. V. Rausch, A. Hansen, E. Solowjow, C. Liu, E. Kreuzer, and J. K. Hedrick, ''Learning a deep neural net policy for end-to-end control of autonomous vehicles,'' in Proc. Amer. Control Conf. (ACC), pp. 4914–4919, May 2017.
[19]. F. Mohseni, S. Voronov, and E. Frisk, ''Deep learning model predictive control for autonomous driving in unknown environments,'' IFAC PapersOnLine, vol. 51, no. 22, pp. 447–452, 2018.
[20]. [Y. Pan, C.-A. Cheng, K. Saigol, K. Lee, X. Yan, E. Theodorou, and B. Boots, ''Agile autonomous driving using end-to-end deep imitation learning,'' in Robotics: Science and Systems. Ithaca, NY, USA: Cornell Univ., 2018.
[21]. S. Sharma, G. Tewolde, and J. Kwon, ''Behavioral cloning for lateral motion control of autonomous vehicles using deep learning,'' in Proc. IEEE Int. Conf. Electro/Inf. Technol. (EIT), pp. 228–233, May 2018.
[22]. T.-D. Do, M.-T. Duong, Q.-V. Dang, and M.-H. Le, ''Real-time self-driving car navigation using deep neural network,'' in Proc. 4th Int. Conf. Green Technol. Sustain. Develop. (GTSD), pp. 7–12, Nov. 2018.
[23]. S. Kuutti, R. Bowden, Y. Jin, P. Barber, and S. Fallah, ''A survey of deep learning applications to autonomous vehicle control,'' IEEE Trans. Intell. Transp. Syst., early access, doi: 10.1109/TITS.2019.2962338, Jan. 7, 2020.
[24]. A. Oussama and T. Mohamed, ''A literature review of steering angle prediction algorithms for self-driving cars,'' in Proc. Int. Conf. Adv. Intell. Syst. Sustain. Develop. Cham, Switzerland: Springer, pp. 30–38, 2019.
[25]. Y. M. Saputra, D. T. Hoang, D. N. Nguyen, E. Dutkiewicz, M. D. Mueck, and S. Srikanteswara. "Energy demand prediction with federated learning for electric vehicle networks", In GLOBECOM. 2019
[26]. Y. Yuan, L. Lei, T. X. Vu, S. Chatzinotas, S. Sun, and B. Ottersten. "Energy minimization in UAV-aided networks: actor-critic learning for constrained scheduling optimization". arXiv preprint arXiv:2006.13610, 2020.
[27]. K. Park, S. Yoon, and E. Hwang. "Flexible charging coordination for plug-in electric vehicles based on uniform stochastic charging demand and time-of-use tariff". In ITEC. 2019.
[28]. X. Guo, T. Liu, B. Tang, X. Tang, J. Zhang, W. Tan, and S. Jin. "Transfer Deep Reinforcement Learning-Enabled Energy Management Strategy for Hybrid Tracked Vehicle". IEEE Access 8, 2020.
[29]. J. Liao, T. Liu, W. Tan, S. Lu, and Y. Yang. "Data-Driven Transferred Energy Management Strategy for Hybrid Electric Vehicles via Deep Reinforcement Learning". arXiv preprint arXiv:2009.03289, 2020.
[30]. T. Liu, X. Tang, X. Hu, W. Tan, and J. Zhang. "Human-like Energy Management Based on Deep Reinforcement Learning and Historical Driving Experiences". arXiv preprint arXiv:2007.10126, 2020.
[31]. S. Ayyadi, M. Maaroufi, and S. M. Arif. "EVs charging and discharging model consisted of EV users behaviour". In REDEC. 2020.
[32]. Y. Xiong, B. Wang, C. Chu, and R. Gadh. "Electric vehicle driver clustering using statistical model and machine learning". In PESGM. 2018.
[33]. L. Zhang, W. Liu, and B. Qi. "Combined Prediction for Vehicle Speed with Fixed Route", Chinese Journal of Mechanical Engineering 33, 1, 2020.
[34]. Peter Ondruska and Ingmar Posner. "Probabilistic attainability maps: Efficiently predicting driver-specific electric vehicle range". In IEEE ITSS. IEEE. 2014.
[35]. E. Martinsson. "WTTE-RNN: Weibull time to event recurrent neural network". Ph.D. Dissertation. Chalmers University of Technology & University of Gothenburg, 2016.
[36]. A.S. Palau, K. Bakliwal, M. H. Dhada, T. Pearce, and A. K. Parlikad. "Recurrent neural networks for real-time distributed collaborative prognostics". In ICPHM. 2018.
[37]. Rose Yu, Yaguang Li, Cyrus Shahabi, Ugur Demiryurek, and Yan Liu. "Deep learning: A generic approach for extreme condition traffic forecasting". In SIAM. SIAM. 2017.
[38]. Jilin Hu, Bin Yang, Chenjuan Guo, Christian S Jensen, and Hui Xiong. "Stochastic origin-destination matrix forecasting using dual-stage graph convolutional, recurrent neural networks". In ICDE. IEEE. 2020.
[39]. Box, G.E.; Jenkins, G.M.; Reinsel, G.C.; Ljung, G.M. "Time Series Analysis: Forecasting and Control"; John Wiley & Sons: Hoboken, NJ, USA, 2015.
[40]. Li, W.; Zhang, Z.-G. "Based on time sequence of ARIMA model in the application of short-term electricity load forecasting". In Proceedings of the 2009 International Conference on Research Challenges in Computer Science, 28–29; pp. 11–14. December 2009.
[41]. Haida, T.; Muto, S. "Regression based peak load forecasting using a transformation technique". IEEE Trans. Power Syst. 9, 1788–1794. [CrossRef], 1994.
[42]. Shankar, R.; Chatterjee, K.; Chatterjee, T.K. "A Very Short-Term Load forecasting using Kalman filter for Load Frequency Control with

Economic Load Dispatch". J. Eng. Sci. Technol. Rev. 5, 97–103. [CrossRef], 2012.
[43]. Park, D.C.; El-Sharkawi, M.A.; Marks, R.J.; Atlas, L.E.; Damborg, M.J. "Electric load forecasting using an artificial neural network". IEEE Trans. Power Syst. 6, 442–449. [CrossRef], 1991.
[44]. Chen, B.J.; Chang, M.W. "Load forecasting using support vector machines: A study on EUNITE competition" IEEE Trans. Power Syst. 2004, 19, 1821–1830. [CrossRef], 2001.
[45]. Hinton, G.E.; Osindero, S.; Teh, Y.W. "A fast learning algorithm for deep belief nets". Neural Comput. 18, 1527–1554. [CrossRef], 2006.
[46]. Hippert, H.S.; Pedreira, C.E.; Souza, R.C. "Neural networks for short-term load forecasting: A review and evaluation". IEEE Trans. Power Syst. 16, 44–55. [CrossRef], 2001.
[47]. Long, J.; Shelhamer, E.; Darrell, T. "Fully convolutional networks for semantic segmentation". In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Boston, MA, USA, 7–12; pp. 3431–3440. June 2015.
[48]. Krizhevsky, A.; Sutskever, I.; Hinton, G.E. "Imagenet classification with deep convolutional neural networks". In Proceedings of the Advances in Neural Information Processing Systems, Lake Tahoe, NV, USA, 3–6; pp. 1097–1105. December 2012.
[49]. Girshick, R.; Donahue, J.; Darrell, T.; Malik, J. "Rich feature hierarchies for accurate object detection and semantic segmentation". In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Washington, DC, USA, 24–27; pp. 580–587. June 2014
[50]. Sutskever, I.; Vinyals, O.; Le, Q.V. "Sequence to sequence learning with neural network". In Proceedings of the Advances in Neural Information Processing Systems, Montreal, QC, Canada, 8–13; pp. 3104–3112. December 2014
[51]. Xydas E, Marmaras C, Cipcipgan L, Jenkins N, Carroll S, Barker M. "A data-driven approach for characterising the charging demand of electric vehicles: a UK case study". Appl Energy; 162:763–71. http://dx.doi.org/ 10. 1016/j. apenergy.2015.10.151. 2016.
[52]. Arias MB, Bae S. "Electric vehicle charging demand forecasting model based on big data technologies". Appl Energy; 183:327–39. http://dx.doi.org/ 10.1016/j.apenergy.2016. 08.080. 2016.
[53]. Moon SK, Kim JO, et al. "Balanced charging strategies for electric vehicles on power systems". Appl Energy 2017; 189:44–54. http://dx.doi.org/10.1016/j. apenergy..12.025. 2016.
[54]. Capasso C, Veneri O. "Experimental study of a DC charging station for full electric and plug in hybrid vehicles". Appl Energy; 152:131–42. http://dx. doi.org/10.1016/ j.apenergy.2 015. 04.040. 2015.
[55]. Deilami S, Masoum AS, Moses PS, Masoum MAS. "Real-time coordination of plug-in electric vehicle charging in smart grids to minimize power losses and improve voltage profile". IEEE Trans Smart Grid;2(3):456–67. http://dx. doi.org/10.1109/TSG.2011.2159816. 2011.
[56]. Richardson DB. "Electric vehicles and the electric grid: a review of modeling approaches, Impacts, and renewable energy integration". Renew Sustain Energy Rev;19:247–54. http://dx.doi.org/10.1016/ j.rser. 2012. 11. 042. 2013.
[57]. Veneri O, Capasso C, Iannuzzi D. "Experimental evaluation of DC charging architecture for fully-electrified low-power two-wheeler". Appl Energy; 162:1428–38. http://dx.doi.org/ 10. 1016/j.apenergy.2015.03.138. 2016.
[58]. Mu Y, Wu J, Jenkins N, Jia H, Wang C. "A Spatial-Temporal model for grid impact analysis of plug-in electric vehicles". Appl Energy; 114:456–65. http://dx. doi.org/10.1016/ j.apenergy.2013.10.006. 2014.
[59]. Bae S, Kwasinski A. "Spatial and temporal model of electric vehicle charging demand". IEEE Trans Smart Grid;3(1):394–403. http:// dx. doi. xorg/10.1109/ TSG.2011. 21592 78. 2012.
[60]. Shrestha S, Hansen TM. "Spatial-temporal stochasticity of electric vehicles in an integrated traffic and power system". In: IEEE EIT int conf. p. 227–32. http://dx. doi. org/10.1109/EIT.2016.7535245. 2016
[61]. Zhou Z, Lin T. "Spatial and temporal for electric vehicle rapid charging demand". In: IEEE VPPC. p. 345–8. http:// dx.doi. org/ 10.1109/ VPPC. 2012.6422675. 2012.
[62]. Viswanathan V, Zehe D, Ivanchev J, Pelzer D, Knoll A, Aydt H. "Simulation assisted exploration of charging infrastructure requirements for electric vehicles in urban environments". J Comput Sci; 12:1–10. http:// dx.doi. org/10.1016/j.jocs.2015.10.012, 2016.
[63]. Yiqi Lu, Yongpan Li, Da Xie, Enwei Wei, Xianlu Bao, Huafeng Chen, Xiancheng Zhong, "The Application of Improved Random Forest Algorithm on the Prediction of Electric Vehicle Charging Load", Energies, 11, 3207; doi:10.3390/en11113207. 2018.
[64]. A. B. Rodríguez, M. R. Wilby, J. J. Vinagre, C. Sánchez, "Modeling and detecting agressiveness from driving signals", IEEE Transactions on Intelligent Transportation Systems, vol. 15, no. 4, pp. 1419-1428, August 2014
[65]. A. Díaz, F. Serradilla, J. J. Anaya, F. Jiménez, J. E. Naranjo, "Estimación de la autonomía de un vehículo eléctrico según el estilo de conducción", Revista DYNA Ingeniería e Industria, 2012

[66]. A. Díaz, F. Serradilla, J. E. Naranjo, J. J. Anaya, F. Jiménez, "Modeling the driving behavior of electric vehicles using smartphones and neural networks", IEEE Intelligent Transportation Systems Magazine, pp. 44- 53, Fall 2014

[67]. Felipe Jimenez, Juan Carlos Amarillo, Jose Eugenio Naranjo, Francisco Serradilla, Alberto Diaz, "Energy consumption estimation in electric vehicles considering driving style", IEEE 18th International Conference on Intelligent Transportation Systems, 101-106, doi 10.1109/ITSC.2015.25, 2015.